

Assignment -1

Machine Learning

Submitted by -

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Q1).

A	B
$\mu_1 = 9.2$	$\mu_2 = 9.6$
$\sigma_1 = 1.6$	$\sigma_2 = 1.2$

a) Given $P(B) = 4P(A)$ and we know that $P(A) + P(B) = 1$

$$\therefore P(A) = \frac{1}{5}, P(B) = \frac{4}{5}$$

Prob. that it was from location A = $\frac{1}{5}$

Prob. that it was from location B = $\frac{4}{5}$

b) $\mu_1 = 9.3, \mu_2 = 8.8, \mu_3 = 9.8$

$$C_1: \mu_1, \mu_2, \mu_3 \rightarrow A \text{ (location A)}$$

$$C_2: \mu_1, \mu_2, \mu_3 \rightarrow B \text{ (location B)}$$

Using Bayes Rule,

$$P(C_i | x) = \frac{P(C_i) \cdot P(x | C_i)}{P(x)}$$

$P(C_1)$: Prior (derived from above question) = $\frac{1}{5}$

$P(x | C_1)$: likelihood

$$P(x = \mu_1, \mu_2, \mu_3 | C_1 = A) = P(\mu_1 | A) * P(\mu_2 | A) * P(\mu_3 | A)$$

As location A rocks are distributed according to a Gaussian distribution, we'll write pdf for gaussian distribution formula -

$$P(\mu_1 | A) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(\mu_1 - \mu_1)^2}{2\sigma_1^2}}$$

$$\therefore P(\mu_1, \mu_2, \mu_3 | A) = \left(\frac{1}{\sqrt{2\pi}\sigma_1}\right)^3 e^{-\frac{1}{2\sigma_1^2} [(x_1 - \mu_1)^2 + (x_2 - \mu_1)^2 + (x_3 - \mu_1)^2]}$$

$$= \left(\frac{1}{\sqrt{2\pi} \cdot (1.6)} \right)^3 \cdot e^{\frac{-1}{2(1.6)^2} [(9.3-9.2)^2 + (8.8-9.2)^2 + (9.8-9.2)^2]}$$

$$= (0.0155)(e^{-0.1035}) = 0.01397$$

$$\begin{aligned} P(x_1, x_2, x_3 | B) &= \left(\frac{1}{\sqrt{2\pi} \sigma_2} \right)^3 e^{\frac{-1}{2\sigma_2^2} [(x_1 - \mu_2)^2 + (x_2 - \mu_2)^2 + (x_3 - \mu_2)^2]} \\ &= \left(\frac{1}{\sqrt{2\pi} (1.2)} \right)^3 e^{\frac{-1}{2(1.2)^2} [(9.3-9.6)^2 + (8.8-9.6)^2 + (9.8-9.6)^2]} \\ &= 0.02812 \end{aligned}$$

$$P(x) = P(c_1) \cdot P(x|c_1) + P(c_2) \cdot P(x|c_2)$$

$$= \frac{1}{5} (0.01397) + \frac{4}{5} (0.02812) = 0.02529$$

$$\therefore P(c_1|x) = \frac{P(c_1) \cdot P(x|c_1)}{P(x)} = \frac{\frac{1}{5} (0.01397)}{0.02529} = 0.11047$$

Thus, probability (posterior) that rocks are from location A is 0.11047.

c) ML hypothesis, $\arg\max_c P(x|c)$ i.e. either $P(x|c_1)$ or $P(x|c_2)$ (whichever is max.)

$$P(x|c_1) = 0.01397$$

$$P(x|c_2) = 0.02812$$

\therefore ML hypothesis is $P(x|c_2) = 0.02812$, where c_2 is that rocks are from location B.

Q2) Screening 1

$$\text{false +ve} = 0.15 \rightarrow P(\text{positive} | \text{No disease}) = 0.15$$

$$P(\text{negative} | \text{No disease}) = 0.85$$

$$\text{false -ve} = 0.10 \rightarrow P(\text{negative} | \text{disease}) = 0.1$$

$$P(\text{positive} | \text{disease}) = 0.9$$

Screening 2,

$$\text{false +ve} = 0.05 \rightarrow P(\text{positive} | \text{no disease}) = 0.05$$

$$P(\text{negative} | \text{no disease}) = 0.95$$

$$\text{false -ve} = 0.03 \rightarrow P(\text{negative} | \text{disease}) = 0.03$$

$$P(\text{positive} | \text{disease}) = 0.97$$

$$P(\text{disease}) = 0.0002$$

$$P(\text{no disease}) = 0.9998$$

a) $X = \{\text{positive}\}_S$,

Compare $P(\text{disease} | X)$ and $P(\text{no disease} | X)$

$$P(\text{disease} | X) = \frac{P(\text{disease}) \cdot P(X | \text{disease})}{P(X)} \quad \text{--- (1)}$$

$$P(\text{No disease} | X) = \frac{P(\text{No disease}) \cdot P(X | \text{No disease})}{P(X)} \quad \text{--- (2)}$$

Comparing numerators from eq (1) & (2),

$$P(\text{disease} | X) = \frac{P(\text{disease}) \cdot P(X | \text{disease})}{P(X)}$$

$$= 0.0002 \times 0.9 = 0.00018$$

$$P(\text{No disease} | X) = \frac{P(\text{No disease}) \cdot P(X | \text{No disease})}{P(X)}$$

$$= 0.9998 \times 0.15 = 0.14997 \quad \text{--- (4)}$$

So, $P(\text{No disease} | X) > P(\text{disease} | X)$

\therefore MAP hypothesis is - person doesn't have a disease
(Bayesian approach)

b) To find ML hypothesis,
 $P(\text{disease} | x)_{s_1} = 0.9$

$$P(\text{No disease} | x)_{s_1} = 0.15$$

\therefore ML hypothesis is \rightarrow Person has a disease.

c) $x = \{\text{positive, positive}\}_{s_1, s_2}$

Posteriori probability that person has a disease?

$$P(\text{Disease} | \text{positive}_{s_1}, \text{positive}_{s_2}) = \frac{P(\text{Disease}) \cdot P(+ve | D)_{s_1} \cdot P(+ve | D)_{s_2}}{P(+ve, +ve)_{s_1, s_2}}$$

$$P(D | s_1, s_2) = \frac{P(D) \cdot P(s_1, s_2 | D)}{P(s_1, s_2)}$$

$$P(s_1, s_2) = P(D) \cdot P(+ve_{s_1}, +ve_{s_2} | D) + P(ND) \cdot P(+ve_{s_1}, +ve_{s_2} | ND)$$

$$= P(D) \cdot P(s_1 | D) \cdot P(s_2 | D) + P(ND) \cdot P(s_1 | ND) \cdot P(s_2 | ND)$$

$$= (0.0002)(0.9)(0.97) + (0.9998)(0.15)(0.05)$$

$$= 0.007673$$

$$P(D | s_1, s_2) = \frac{0.0002 \times 0.9 \times 0.97}{0.007673} = 0.0228$$

Posteriori prob. that a person has disease is 0.0228

Q3. $P(H) = \theta$, $P(T) = 1 - \theta$

we get TTHTTH

a) $P(TTHTTH) = (1-\theta)^4 \theta^2$ $\{= P(T); P(T) \cdot P(H) \cdot P(T) \cdot P(T) \cdot P(H)\}$

b) $\log P(TTHTTH) = \log \{(1-\theta)^4 \theta^2\} = 4 \log(1-\theta) + 2 \log \theta$

c) ML estimate of $\theta = \underset{\theta}{\operatorname{argmax}} P(TTHTTH | \theta)$; need to compute $\underset{\theta}{\operatorname{argmax}} \log P(TTHTTH | \theta)$

Partial derivative of $\log P(TTHTTH)$ w.r.t θ shd be zero.

$$\frac{\partial \log P(TTHHTTH)}{\partial \theta} = \frac{\partial (4 \log(1-\theta) + 2 \log \theta)}{\partial \theta} = 4 \frac{\partial \log(1-\theta)}{\partial (1-\theta)} \cdot \frac{\partial (1-\theta)}{\partial \theta} + 2 \frac{\partial \log \theta}{\partial \theta}$$

$$\Rightarrow \frac{2}{\theta} - \frac{4}{1-\theta} = 0$$

$$= 4(-1) + \frac{2}{\theta} = 0$$

$$\Rightarrow 2(1-\theta) - 4\theta = 0$$

$$\Rightarrow 2 - 6\theta = 0 \Rightarrow \theta = 1/3$$

ML estimate is at $\theta = 1/3$.

Q4.

a) $S=3$, $X = \{3, 1, 1, 2, 3\}$

$$\theta_1 = \theta_v \therefore v=1$$

$$\therefore \frac{t}{N} = \frac{2}{5} \text{ is ML estimate.}$$

b) ~~$m=2$~~ , here, $m=1$, \therefore ML estimate $\frac{t+1}{N+5} = \frac{2+1}{5+5} = \frac{3}{10} = 0.375$

c) $S=2$ (possible values of x)

$N \rightarrow$ # values in set

$t \rightarrow$ # occurrences of 1

$$\theta_1 = \theta_v \Rightarrow v=1$$

Given N independent occurrences where possible values of x can be only 2 $\Rightarrow P(x|\theta) = \theta^t (1-\theta)^{N-t} \therefore P(x|\theta_1) = \theta_1^t (1-\theta_1)^{N-t}$

$$\text{Given } \rightarrow P(\theta_1) = 6\theta_1(1-\theta_1), \theta_{\text{map}} = \arg\max_{\theta} P(\theta_1) \cdot P(x|\theta_1)$$

$$= \arg\max_{\theta} 6\theta_1(1-\theta_1)\theta_1^t(1-\theta_1)^{N-t} = \arg\max [\log 6 + (t+1)\log \theta_1 + (N-t+1)\log(1-\theta_1)]$$

Differentiating w.r.t θ

$$\frac{d}{d\theta} \Rightarrow \frac{t+1}{\theta_1} - \frac{(N-t+1)}{(1-\theta_1)} \therefore \frac{t+1}{\theta_1} = \frac{N-t+1}{1-\theta_1} \Rightarrow \theta_1 = \frac{t+1}{N+2}$$

Also, given $S=2$, comparing with estimate (2), $S=2$ & $m=1$ (add-1-smoothing)

$$\theta_1 (\text{estimate ii}) = \frac{t+1}{N+5}$$

Also, true for m smoothing ($m \in [0, 1]$), $\theta_1 (\text{estimate iii}) = \frac{t+m}{N+5m}$

Solution (5)

Classes : $C_1 = +$

$C_2 = -$

$x_1 \rightarrow \{ \text{low, Medium, High} \}$

$x_2 \rightarrow \{ \text{Yes, No} \}$

$x_3 \rightarrow \{ \text{Red, Green} \}$

a) Add m -smoothing is given by formula,

$$P(x|C) = \frac{\text{count}(x,C) + m}{\text{count}(C) + (m \times \text{possible values of } x)}$$

Using above, (Given $m=0.3$)

$$\begin{aligned} P(x_1 = \text{low} | +) &= \frac{1 + 0.3}{2 + (0.3 \times 3)} \\ &= 0.4483 \end{aligned}$$

$$\begin{aligned} P(x_2 = \text{Yes} | +) &= \frac{0 + 0.3}{2 + (0.3 \times 2)} \\ &= 0.1154 \end{aligned}$$

$$\begin{aligned} P(x_3 = \text{Green} | +) &= \frac{1 + 0.3}{2 + (0.3 \times 2)} \\ &= 0.5 \end{aligned}$$

$$\begin{aligned} \text{count}(\text{low}, +) &= 1 \\ \text{count}(C)_+ &= 2 \\ \text{count}(x_1) &= 3 \end{aligned}$$

$$\begin{aligned} \text{count}(\text{Yes}, +) &= 0 \\ \text{count}(C)_+ &= 2 \\ \text{count}(x_2) &= 2 \end{aligned}$$

$$\begin{aligned} \text{count}(\text{Green}, +) &= 1 \\ \text{count}(C)_+ &= 2 \\ \text{count}(x_3) &= 2 \end{aligned}$$

Q5. continued ...

$$P(x_1 = \text{low} | -) = \frac{1 + 0.3}{3 + (0.3 \times 3)} = 0.3333$$

$$P(x_2 = \text{yes} | -) = \frac{2 + 0.3}{3 + (0.3 \times 2)} = 0.6389$$

$$P(x_3 = \text{Green} | -) = \frac{2 + 0.3}{3 + (0.3 \times 2)} = 0.6389$$

$$\text{count}(\text{low}, -) = 1$$

$$\text{count}(c)_- = 2$$

$$\text{count}(x_1) = 3$$

$$\text{count}(\text{yes}, -) = 2$$

$$\text{count}(c)_- = 3$$

$$\text{count}(x_2) = 2$$

$$\text{count}(\text{Green}, -) = 2$$

$$\text{count}(c)_- = 3$$

$$\text{count}(x_3) = 2$$

b) Comparing $P(x|+)$ and $P(x|-)$

where, $x = \{\text{low, yes, green}\}$, $P(+) = \frac{2}{5}$, $P(-) = \frac{3}{5}$

By using Naive - Bayes assumption

$$P(x|c) = P(x_1 = \text{low} | c) * P(x_2 = \text{yes} | c) * P(x_3 = \text{green} | c)$$

$$P(x|+) = 0.4483 \times 0.1154 \times 0.5 = 0.0259$$

$$P(x|-) = 0.3333 \times 0.6389 \times 0.6389 = 0.13605$$

c) ML hypothesis

From b) we can say $P(x|-) > P(x|+)$

\therefore ML label for $x \{\text{low, yes, green}\}$ is -

d) MAP hypothesis

$$P(+) = \frac{2}{5}, P(-) = \frac{3}{5}$$

$$P(x|c) = P(c) \cdot P(x_1 = \text{low} | c) * P(x_2 = \text{yes} | c) * P(x_3 = \text{green} | c)$$

$$P(x|+) = \frac{2}{5} \times 0.0259 = 0.01036$$

$$P(x|-) = \cancel{\frac{3}{5}} \times \cancel{0.13605} = \frac{3}{5} \times 0.13605 = 0.08163$$

$P(x|-) > P(x|+)$, MAP hypothesis $\rightarrow P(x|-)$

MAP label for $x \{\text{low, yes, green}\}$ is -